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A review of solar energy modeling techniques

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ABSTRACT

Solar radiation data provide information on how much of the sun's energy strikes a surface at a location on the earth during a particular time period. These data are needed for effective research in solar-energy utilization. Due to the cost of and difficulty in solar radiation measurements and these data are not readily available, alternative ways of generating these data are needed. In this paper, a review is made on the solar energy modeling techniques which are classified based on the nature of the modeling technique. Linear, nonlinear, artificial intelligence models for solar energy prediction have been considered in this review. The outcome of the review showed that the sunshine ratio, ambient temperature and relative humidity are the most correlated coefficients to solar energy.

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1. Introduction

Solar energy is the portion of the sun's energy available at the earth's surface for useful applications, such as exciting electrons in a photovoltaic cell and supplying energy to natural processes like photosynthesis. This energy is free, clean and abundant in most places throughout the year and is important especially at the time of high fossil fuel costs and degradation of the atmosphere by the use of these fossil fuels. Solar energy consists of two parts; extraterrestrial solar energy which is above the atmosphere and global solar energy which is under the atmosphere. The global solar energy incident on a horizontal surface may have direct beam and diffuse solar energy. Diffuse solar energy is usually measured by pyranometers, solarimeters, or actinography while direct beam solar radiation is measured by a pyrheliometer. These measuring devices are usually installed at selected sites in specific region and it is not feasible to install at many sites due to high cost of these devices. In addition, these measuring devices have tolerance and accuracy and consequently wrong/missing records may be found in the data set. The measured solar energy values can be used for developing solar energy models which describes the mathematical relations between the solar energy and the meteorological variables such as ambient temperature, humidity and sunshine ratio. These models can be later used to predict the direct and diffuse solar energy using historical metrological data at sites where there is no solar energy measuring device installed [1].

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Many solar energy models have been presented in the literature using mathematical linear [2–9] and nonlinear functions [10–16], artificial neural network [17–27] and fuzzy logic [28,30]. An important aspect in modeling solar energy is the accuracy of the developed model which is evaluated using statistical errors such as the mean absolute percentage error (MAPE), mean bias error (MBE) and root mean square error (RMSE) [8]. The MAPE is an indicator of accuracy in which it expresses the difference between real and predicted values to the real value. The calculated MAPE is summed for every fitted or forecasted point in time and divided again by the number of fitted points, n. MBE is an indicator for the average deviation of the predicted values from the measured data. A positive MBE value indicates the amount of overestimation in the predicted global solar energy and vice versa. On the other hand, RMSE provides information on the short-term performance of the model and is a measure of the variation of the predicted values around the measured data. RMSE also shows the efficiency of the developed model in predicting future individual values. A large positive RMSE implies a big deviation in the predicted value from the measured value.

However, some reviewing work in regards to solar energy models can be found in [31–34]. All these papers focus on linear and non linear models for solar energy while other novel techniques such as ANN and fuzzy logic techniques are missing. Therefore this paper presents an overview of the past and current research works related to development of solar energy modeling techniques. The use of linear and nonlinear modeling techniques as well as artificial intelligent techniques for modeling solar energy is first described and then a comparison of these techniques is presented. Lastly, the models that are being used for modeling of solar energy on tilt surface is discussed.

2. Solar energy model using linear and nonlinear modeling techniques

The commonly used solar energy models developed in the past are based on linear and nonlinear models [1]. These models give a correlation between solar energy on a horizontal surface and some meteorological variables such as shining hours, ambient temperature and relative humidity. The linear models use simple linear function while the nonlinear models use polynomial function of the third or fourth degree.

2.1. Global solar energy model

Linear or nonlinear models can be used to calculate the global solar energy in terms of the sun shine hours. A commonly used linear model for this purpose which defines the global solar energy in terms of the extraterrestrial solar energy is given by [2],

$$\frac{E_T}{E_{extra}} = a + b\frac{S}{S_o} \tag{1}$$

where E_T, E_{extra}, S, and S_o are global solar energy, extraterrestrial solar energy, day length and number of shining hours, respectively.

Global solar energy models developed using linear functions can be found in the literature. In [3], a linear model of global solar energy has been developed using the solar radiation data for three locations in Malaysia and linear regression analysis. In [4], the developed solar energy model using the monthly solar radiation for eight locations in Malaysia is based on the least square linear regression analysis. In [5], a simple linear model for global and diffuse solar radiation was done for Bangkok, Thailand. Linear modeling of global solar radiation was done by using the Angström model for the northwestern part of Turkey [6]. Two global solar energy models using the Angström model and the Hargreaves model have been developed for the three zones in Nigeria [7]. The models' coefficients were calculated by plotting the clearness index versus the possible sunshine hours. In [8], the global solar energy model for Malaysia has been developed using the Angström model. All the above-mentioned global solar energy models based on the Angström model determine the model coefficients by using the MATLAB fitting tool. For better estimation of the coefficients, the model parameters, a and b are seasonally changed [9]. For developing a more accurate global solar energy model, considerations are made on the clouds and atmospheric conditions to the solar radiation estimation and the use of Angström model with a modified day-length instead of considering the sun shine hours and solar energy that first hits the ground. A nonlinear term is added to the Angström model to obtain the quadratic model [10] which is given by,

$$\frac{E_T}{E_{extra}} = a + b\frac{S}{S_o} + c\left(\frac{S}{S_o}\right)^2 \tag{2}$$

A simple regression model for global solar radiation in terms of clearness and diffuse indices for North Sinai, Egypt has been presented [11]. In [12], a nonlinear model was used for modeling the global solar radiation in terms of sunshine ratio for Istanbul, Turkey. In [13], linear and nonlinear forms of Angström model were employed to model the global solar radiation on horizontal surfaces in Jeddah, Saudi Arabia. The global solar radiation is in terms of ambient temperature, relative humidity and sunshine hours. For modeling the global solar energy on a tilt surface, the Liu and Jordan model was used.

2.2. Diffuse solar energy model

The relationship between the average daily diffuse and global solar radiations incident on a horizontal surface and the sky clearness index can be found from direct meteorological observations or through an empirical relationship [14]. Many linear models used the relation between E_d/E_T and the clearness index, K_T to calculate the diffuse solar energy which is expressed as follows,

$$\frac{E_d}{E_T} = a + bK_T \tag{3}$$

where E_d, E_T, and K_T are the diffuse solar energy, global solar energy and clearness index, respectively. a and b are coefficients of the model.

This linear expression, which represents the diffuse solar energy in terms of global solar energy and clearness index is used for modeling diffuse solar energy in [8,15]. However, the same relationship between E_d/E_T and the clearness index K_T can be described by the following non-linear model.

$$\frac{E_d}{E_T} = a + bK_T + cK_T^2 + dK_T^3 \tag{4}$$

The use of Eq. (4) can be found in [8,14,15]. In [16], a linear regression model has been applied for modeling diffuse solar radiation in Guangzhou, China. The developed model is in terms of global solar radiation, ambient temperature, relative humidity, clearness index and sunshine ratio. An extraterrestrial solar radiation model in terms of the same parameters has been developed and compared with other linear and nonlinear models that do not take into account temperature and humidity.

3. Solar energy model using artificial intelligent techniques

Solar energy models using artificial intelligent techniques can be found in [17–38]. In [17], artificial neural network (ANN) was used to estimate the global solar radiation for selected sites in Saudi Arabia. Data from 41 stations were obtained to develop the ANN based solar energy model. The ANN model employed is the

multi-layer feed forward neural network (MLFFNN) and the training algorithm is based on the back propagation algorithm. The developed MLFFNN consists of 4 input neurons, 10 neurons in the hidden layer and 1 output neuron. The inputs to the MLFFNN are the latitude, longitude, altitude and sunshine duration. The accuracy of the developed MLFFNN in terms of the average MAPE is 12.6%. In [18], a MLFFNN trained by the back propagation algorithm was also developed to predict the global solar radiation for sites in Oman in terms of location, month, mean pressure, temperature, vapor pressure, relative humidity and sunshine duration. The MAPE for the developed model is found to be 7.3%. In [19], MLFFNN with back propagation algorithm was employed for estimating the total solar radiation in Greece. A multilayer recurrent neural network with back-propagation training algorithm was applied for predicting the solar radiation in Cyprus [20]. Here, the ANN input variables are the month, day of month, Julian day, season, mean ambient temperature and mean relative humidity. In [21], ANN has been developed for modeling monthly global solar energy for 12 sites in Turkey using 3 years data. The developed model aims to predict the solar energy at sites where no monitoring devices are installed. The input variables to the ANN are the geographical and metrological variables such as latitude, longitude, altitude, month, sunshine ratio and temperature. For ANN training, the scaled conjugate gradient, Pola-Ribiere conjugate gradient, Levenberg–Marquardt learning algorithm and logistic sigmoid transfer function were used in training the developed model. The average MAPE of the developed ANN model was found to be 6.78%. However, the disadvantages of the developed ANN method are that it is not accurate because it uses short term data and considers monthly average solar energy that does not help in designing accurate solar energy systems which require daily or hourly average solar energy. In [22], a feedback propagation neural network model has been developed using 195 cites data for Nigeria. Here, the ANN input variables are the latitude, longitude, altitude, month, sunshine ratio, temperature and relative humidity. The developed ANN model is then used for obtaining solar maps of Nigeria for all months. In [23], the MLFFNN was employed to estimate the daily global solar radiation in China. The inputs to the neural network are the latitude, longitude, altitude day number, temperature and sunshine ratio. The accuracy of the developed MLFFNN is evaluated and found to give RMSE value in the range of (9.1–20.5)% and MBE values in the range of 16.9% underestimation to 18.6% overestimation.

ANN has also been applied for predicting global solar radiation in terms of sunshine hours and ambient temperature in Algeria [24]. Similarly, an ANN model using the back propagation training algorithm has been developed for estimating the monthly, daily and hourly global solar radiation for selected sites in India [25]. The input parameters to the ANN that have been considered for estimating the solar radiation for each city are; latitude, longitude, altitude, month, time, air temperature, wind speed, relative humidity and rainfall. The developed ANN is found to give maximum mean absolute relative deviation of predicted hourly global radiation of 4.07%. In [26], the radial basis function neural network model is used to model the global solar radiation in Al-Madinah, Saudi Arabia. The input parameters to the ANN are the air temperature, sunshine ratio and relative humidity. The global solar radiation results show that there is a strong correlation between the global solar radiation and the sunshine ratio compared to the temperature and humidity. The developed ANN model is then used for predicting the global solar radiation in terms of sunshine ratio and temperate with accuracy of average MAPE, MBE and RMSE values of 1.75%, 0.0131% and 0.8748%, respectively. From the works reported in [17–26], it is noted that there are variations in the selection of the input variables to the ANN. The commonly used input variables are the sunshine ratio, ambient temperature and relative humidity to predict global solar energy at different locations.

In [27], the feed forward MLP neural network model considering four inputs and one output has been developed to predict the global solar radiation. The inputs to the ANN are the latitude, longitude, day number and sunshine ratio while the output is the clearness index. Data from 28 weather stations were considered for the development of the ANN model in which data from 23 stations were used for training and data from 5 stations were used for testing the ANN. The ANN results for predicting the global solar radiation give average MAPE, MBE and RMSE of 5.92%, 1.46% and 7.96%, respectively. In [28], a multi-layer perceptron (MLP) neural network using the back propagation training algorithm is applied for modeling hourly solar radiation for seven sites in Spain. This model is used for generating a time series of hourly solar radiation for sites at which no measuring devices are available.

Development of diffused and beam solar energy models using ANN can be found in [8,29–36]. In [29], ANN and fuzzy logic were used to predict the hourly global solar radiation in fifteen Spanish terrestrials using the satellite images and cloud index. For predicting the global solar radiation, the cleanness index which is a function of the cloud index has to be estimated using four alternative models, namely, simple regression model, extended regression model, fuzzy logic model and ANN model. It is proven that the fuzzy logic and ANN models give accurate prediction of the clearness index compared to the regression models. Fuzzy logic was also applied for predicting solar energy where there are ambiguities and vagueness in solar energy and sunshine duration records in a day [30]. The main advantage of the fuzzy logic model is that it can be devised for handling uncertainties in estimating the solar radiation. A detailed description of the fuzzy sets and fuzzy logic implementation for solar energy estimation can be found in [30]. In the fuzzy logic implementation, the solar energy variables which are sunshine duration and solar energy are described in terms of linguistic variables such as long, high, short, and small.

ANN model has been developed for estimating the diffuse solar energy in which the inputs of the model are cleanness index, day number and latitude and longitude coordinates [8]. In [35], two MLP neural networks with the back propagation training algorithm are used for predicting the hourly and daily diffuse solar radiation for selected sites in Egypt. The ANN model for predicting the hourly diffuse radiation has six inputs which are the hour, day, month, year, hourly global radiation and hourly extraterrestrial solar radiation. Meanwhile, the ANN model for predicting the diffuse solar radiation has three inputs, namely, global solar radiation, extraterrestrial solar radiation and sun shine ratio. The results of the study showed that the ANN based models are more accurate in predicting the diffuse radiation compared to the linear regression models. In [36], a MLP neural network was also developed for predicting the direct solar radiation for selected sites in India. The predicted direct solar radiation is in terms of the latitude, longitude, altitude, month, sun shine ratio, rainfall and humidity.

4. Comparison of solar energy prediction models

In this section, a comparison between the reviewed solar energy modeling techniques, namely, linear, nonlinear and ANN models is presented in terms of the prediction accuracy. Tables 1 and 2 show the accuracy of the linear, non-linear, fuzzy logic and ANN models

Table 1
Average values of MAPE, RMSE and MBE for the global solar energy model [8].

	MAPE	RMSE	RMSE (%)	MBE	MBE (%)
Liner model	8.13	0.44	9.32	−0.014	−0.30
Nonlinear model	6.93	0.41	8.73	−0.013	−0.31
Fuzzy logic model	6.71	0.42	8.80	0.019	0.32
ANN model	5.38	0.35	7.37	−0.019	−0.42

Table 2
Average values of MAPE, RMSE and MBE for the diffuse solar energy models [8].

	MAPE	RMSE	RMSE (%)	MBE	MBE (%)
Linear model	4.35	0.146	5.22	0.003	0.094
Nonlinear model	3.74	0.136	4.85	0.003	0.090
ANN model	1.53	0.056	2.01	−0.0009	−0.062

for predicting the global and diffuse solar energy models, respectively, for five sites in Malaysia [8]. From the table, the ANN model is the most accurate model for solar energy prediction in which the MAPE values for ANN based global and diffuse solar energy models are 5.38% and 1.53%, respectively. However, the MAPE values for the linear, nonlinear and fuzzy logic models for the global solar energy are 8.13%, 6.93% and 6.71%, respectively, while the MAPE values for the linear and nonlinear models for the diffuse solar energy are 4.35% and 3.74%, respectively.

On the other hand in [37] a comparative study is conducted between Angström model and the ANN mode. The developed ANN models have two metrological variables as inputs namely sun shine ratio and ambient temperature. However, the authors claimed that for most of the models, the MBE values are comparable and it cannot be considered as decisive for the prevalence of any one of the models. Meanwhile RMSE of the ANN based models is lower than the one which is for Angström based models and therefore, the authors recommended the ANN model for such purpose. In [38], a comparison was made on various ANN models, namely, radial basis function (RBF) neural network, feed forward neural network (FFNN), Elman recurrent network (ELM) and adaptive neuro fuzzy inference system (ANFIS) for predicting hourly solar radiation. The inputs to the ANN models are the wind speed and direction, temperature and pressure. The hidden neurons for the FFNN, ELM and RBF are 4, 6 and 25, respectively, while for the ANFIS model, two Gaussian membership functions per variable are used. The ANN training algorithms are the back propagation algorithm and the Levenberg Marquardt (LM) algorithm. It was claimed that the ANN trained by the LM algorithm gave more accurate prediction results compared to the models trained by the back propagation algorithm.

5. Modeling of solar energy on a tilt surface

The solar energy models that have been described in the previous sections are for solar energy on horizontal surface, but here models of solar energy on tilt surface are considered. The aim of modeling of solar energy on a tilt surface is to find the optimum tilt angle of a solar collector in a specific region. As a matter of fact, the orientation and the tilt of a solar panel strongly affect the amount of the collected yield. Therefore, solar panels must be slanted and oriented at optimum angles so as to collect the maximum solar energy available in a specific region. The best method to optimize the tilt and the orientation of a solar panel is by applying an active sun tracker. Active sun trackers are electromechanical or pure mechanical devices that keep changing the tilt and the orientation of a solar panel/solar array periodically during the day. However, the capital cost of such a system is high and it consumes energy during tracking. Thus, changing the tilt angle and the orientation monthly, seasonal or yearly for a PV panel may be more feasible than applying an active sun tracker [1].

To predict the solar energy on a surface, the solar energy on horizontal surface and geometrical models are considered. Therefore, the components of incident global solar radiation on a tilt surface consider the global, direct (beam), diffuse and reflected solar energy on a tilt surface. The solar energy components on a tilt surface are given by,

$$E_{T_{TLT}} = (E_T - E_D)R_B + E_D R_D + E_T \rho R_R \tag{6}$$

where R_B, R_D and R_R are coefficients and ρ is ground Aledo. R_B is the ratio between global solar energy on a horizontal surface and global solar energy on a tilt surface. R_D is the ratio between diffuse solar energy on a horizontal surface and diffuse solar energy on a tilt surface and R_R is the amount of reflected solar energy on a tilt surface.

From Eq. (6), it is clear that to determine the solar energy components on a tilt surface is to estimate the coefficients R_B, R_D and R_R. The most commonly used model for calculating R_B is by using the Liu and Jordan model [39] which defines R_B as

$$R_B = \frac{\cos(LAT - TLT)\cos DEC \sin\ \ \omega_{ss} + \omega_{ss}\ \ \sin(LAT - TLT)\sin DEC}{\cos LAT \cos DEC \sin\ \ \omega_{ss} + \omega_{ss}\ \ \sin LAT \sin DEC} \tag{7}$$

where LAT is the latitude of the location and TLT is the tilt angle. DEC and ω_{ss} are the declination angle and sun shine hour angle, respectively.

The equation of R_R is given by,

$$R_R = \frac{1 - \cos TLT}{2} \tag{8}$$

For estimating R_D the isotropic and anisotropic solar energy models have been used.

5.1. Isotropic diffuse solar energy model

Isotropic solar energy models are based on the hypothesis that isotropic radiation has the same intensity regardless of the direction of measurement, and an isotropic field exerts the same action regardless of how the test particle is oriented. It radiates uniformly in all directions from a point source sometimes called an isotropic radiator. One of the most well-known isotropic diffuse solar models is the Liu and Jordan model [39] with R_D being formulated as,

$$R_D = \frac{1 + \cos TLT}{2} \tag{9}$$

Meanwhile, Koronakis [40] proposed a new formula for R_D as follows,

$$R_D = \frac{1}{3[2 + \cos TLT]} \tag{10}$$

Badescu [41] recommended R_D as,

$$R_D = \frac{3 + \cos(2TLT)}{4} \tag{11}$$

Tian et al. [42] defined R_D as,

$$R_D = 1 - \frac{TLT}{180} \tag{12}$$

5.2. Anisotropic solar energy models

Anisotropy is the property of being directionally dependent, as opposed to isotropy which implies identical properties in all directions. Therefore, anisotropic solar energy models are based on the hypothesis that anisotropic radiation has different intensity depending on the direction of measurement and it radiates non uniformly in all directions. Hay [43] defined R_D as,

$$R_D = \frac{E_T - E_D}{E_T} R_B + \left(1 - \frac{B}{G}\right)\left(\frac{1 + \cos TLT}{2}\right) \tag{13}$$

Steven and Unsworth [44] suggested a different equation to calculate R_D as,

$$R_D = 0.51 R_B + \frac{1 + \cos TLT}{2} - \frac{1.74}{1.26\pi}\left[\sin TLT = \left(TLT\frac{\pi}{180}\right)\cos TLT - \pi \sin^2\left(\frac{TLT}{2}\right)\right] \tag{14}$$

Arvid and Asle [45] defined R_D as

$$R_D = \frac{E_T - E_D}{E_T} R_B + \varphi \cos TLT + \left(1 - \frac{B}{G} - \varphi\right)\left(\frac{1+\cos TLT}{2}\right) \quad (15)$$

Finally, Reindl et al. [46] recommended the following equation for calculating R_D

$$R_D = \frac{E_T - E_D}{E_T} R_b + \left(1 - \frac{E_T - E_D}{E_T}\right)\left(\frac{1+\cos TLT}{2}\right) \times \left(1 + \sqrt{\frac{E_T - E_D}{E_T}} \sin^3\left(\frac{TLT}{2}\right)\right) \quad (16)$$

5.3. Methods for calculating optimum tilt angle

In recent years, many research works have been developed with the objective of optimizing the tilt and orientation angles at specific regions [47–60]. In [47], the optimum tilt angle of a solar panel for Madinah, Saudi Arabia was calculated using historical data. The total solar irradiation versus tilt angle for each month was used to fit the curves represented by second order polynomial equations. These polynomial equations were differentiated with respect to the tilt angle and then equated to zero to obtain the optimum tilt angle. In [48], a method to predict solar energy on a tilt surface in Ajaccio, France has been presented by calculating the horizontal diffuse solar radiation from the horizontal global solar radiation. The global solar radiation on a tilted plane is calculated using both global and diffuse solar radiations on a horizontal plane. The optimum tilt angle for sites in China has been calculated by estimating the diffuse radiation on a horizontal surface based on a linear model [49]. Then, global and diffuse solar radiation incident on a tilt surface is calculated. In [50], the calculated optimum tilt angle for Sanliurfa, Turkey and applied for a dual axis sun tracker. The output of the tracking PV module was compared with an identical PV module but with zero tilt angles. In [51], the optimum tilt angle range for Egypt was calculated based on an evaluation of the PV module output power under different tilt angles. The theoretical aspects of choosing the tilt angle for Egypt were then examined [51]. A statistical comparison of three specific solar models was performed to determine an accurate model for estimating the solar radiation falling on an inclined surface. The solar energy model that provides the most accurate estimation of the total solar radiation was used to determine the optimum collector slope based on the maximum solar energy availability. In [52], the optimum tilt angle for solar panels in Syria was calculated using the instantaneously extraterrestrial radiation fall on a tilt surface. In [53], the optimum tilt angle for solar panels in Dhaka was calculated using three solar models. In [54], the optimum tilt angle for Burgos, Spain was calculated by considering isotropic models. The results obtained using the isotropic models were tabulated and plotted against the tilt angle for summer, winter and all year. The optimum tilt angle and the solar radiation on a south facing tilted surface were calculated for different periods of time by using three different models.

In [55], the optimum angle was computed by searching for the values for which the total radiation on the collector surface is a maximum for a particular day or a specific period in Brunei Darussalam. In [56], recorded data and selected model were used to construct a data base that contains the averages and the variances of the hourly global solar irradiance on tilted surfaces over specific periods of time, for various tilt angles and orientations. The constructed data base is utilized to produce meta models that correlate tilt angle and orientation with mean global irradiance and its variance on tilted surfaces. Then, an optimization problem is formulated, aiming to determine the optimum values of tilt angle and orientation. In [57], the optimum angle was calculated by searching for the values for which the total radiation on the collector surface is a maximum for a particular day or a specific period. An application of the model was done using the experimental data measured for Izmir in Turkey. In [58], an approach employing sky radiance models was applied for determining the optimal tilt angle of solar collectors with respect to a set of geographic latitudes. In [59], calculation of the yearly optimum angle for Sabah and Sarawak was done. However, the calculated optimum tilt angle value is not applicable for the whole region in Malaysia because of the differences in the location coordinates. In [60], optimum tilt angle for solar panels in Malaysia were calculated by considering five sites in Malaysia. The optimum tilt angles are calculated for the monthly and seasonal periods using historical data (1975–2005) for global and diffuse solar radiation. A generalization of the results for all Malaysia is also done so as to draw a map of optimum tilt angle for Malaysia.

6. Challenges in modeling solar energy

In modeling solar energy, the issues that need to be considered and the challenges faced are described as follows:

(a) Prediction accuracy – the most important issue in solar energy modeling is the accuracy of the predicted value. Recently, the heuristic optimization techniques have been proven to overcome this problem because the techniques are able to predict the solar energy accurately compared to other linear and nonlinear optimization techniques.
(b) Model simplicity – in the past, the simplicity of the models played a very important role in choosing the models. For example, the nonlinear models are more accurate than the linear models but the calculation of the linear models coefficients is simpler. However, the uses of mathematical software tool such as that available in MATLAB facilitate the calculation of the model coefficients by using the fitting tools.
(c) Models inputs – from the literature, most authors used sunshine ratio, ambient temperature and relative humidity as input variables to the developed models. However, none of these authors discuss the probability of having the ambient temperature, relative humidity and sunshine hour's variables for a site without having the solar energy data although most of the current weather stations contain comprehensive measuring devices and this obstacle still facing the solar energy.
(d) Availability of data – to obtain an accurate solar energy prediction model, a long term weather data are required. However, such data are not easily available because of the high cost of measuring devices and the difficulty in accessibility of the measuring sites.
(e) Architecture of the ANN models – from the literature, the ANN is considered the most appropriate model for solar energy prediction. However, the process in calculating the optimum number of hidden neurons in an ANN model is still a challenge because it is based on the trial and error approach.

7. Conclusion

Reviews on solar energy modeling and prediction techniques used have been extensively studied. The solar energy modeling techniques used are classified based on the nature of the modeling technique. Linear, nonlinear and artificial intelligence modeling techniques for solar energy prediction have been studied in this review. From the review, the sunshine ratio, ambient temperature and relative humidity are the most correlated coefficients for predicting solar energy. It is also noted that the ANN models are the most accurate methods for predicting solar energy compared to the linear and nonlinear models.

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